Peer pressure enables actuation of mobility lifestyles ☆

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ABSTRACT

This paper explores the utility of peer pressure as an actionable mechanism to induce socially responsible and environmentally-conscious mobility habits. We adopt a two-stage game theoretic model of peer pressure to investigate feedback between social, geographic, and temporal dimensions of agent choices in a hyper-realistic micro-simulation of travel. The results show that peer pressure helps in achieving desirable equilibrium properties while reducing congestion and emissions due to sustained mode shift. With a way to initiate the required social norming and a proper concern for privacy and ethics, these cost-effective mechanisms may soon begin to find use in improving community welfare.

1. Introduction

Surging interest and political acceptance of behavioral interventions, or *nudges*, have created novel opportunities for transportation planners to strategically structure mobility choice architectures that actuate and stabilize environmentally-beneficial mobility lifestyle changes (Leonard et al., 2008; Avineri, 2012). Voluntary travel behavior change and personal travel planning have been in use since the 1980s to persuade commuters to engage in pro-environmental and pro-social travel behaviors (Fujii and Taniguchi, 2006). More recently, ubiquitous, networked computing technologies and social media channels have provided additional outlets to motivate and sustain behavior change (Jariyasunant et al., 2015; Gaker et al., 2010, 2011). While empirical and theoretical evidence suggests social norms and personalized feedback can reinforce positive attitudes towards sustainable mode choice (Brög et al., 2009), little work has been done to rigorously and independently evaluate the costs and benefits of novel behavioral policy alternatives (te Brömmelstroet, 2014; Bonsall, 2009).

Simulations of cyber-social influence on travel decision-making may help transit agencies quantitatively and transparently justify to stakeholders programs intended to incentivize peer-to-peer influence as a means of encouraging socially cooperative modality lifestyles. Herein, we adapt a two-stage game theoretic model of peer pressure inspired by Mani et al. (2013) to investigate how feedback between social, geographic, and temporal dimensions in agent-based simulations of travel can motivate pro-environmental transportation decisions. This work extends related research on joint-decision making as well as the cost-benefit analysis of policy incentives to internalize the environmental externalities of transportation (Illenberger, 2012; Dubernet and Axhausen, 2013; Axhausen, 2007; Agarwal et al., 2015; Hackney and Marchal, 2011; Kaddoura et al., 2017; Kickhöfer and Kern, 2015). The software implementation of our model is built on top of the open-source microsimulation software, MATSim, which was chosen for its compatibility with behavioral choice theories, modularity, and ability to handle large heterogeneous populations of agents (Horni et al., 2016).

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We verify our system on a scenario situated in the San Francisco Bay Area in California. By monetizing reductions in emission and congestion externalities, we evaluate the effect of potential policy instruments intended to motivate agents to influence their peers to use public transit instead of commuting to work alone. While experimental results are focused on public transportation as an alternative mode, the game-theoretic setting and experimental simulation developed by this work covers a wide class of situations characterized by a high price of anarchy (Koutsoupias and Papadimitriou, 2009; O'Hare et al., 2016) where selfish behaviors (such as driving alone) curtail system performance.

2. Related work

By definition, *common pool resources* are freely-available and ungoverned (Ostrom, 2010). *The tragedy of the commons* may occur when a common pool resource is depleted to the extent that each' additional unit of consumption reduces the value of the resource for the entire society (Hardin, 1968). The tragedy of the commons has been frequently studied in the economics, control, and distributed artificial intelligence communities using game theoretic models representing agent decision-making related to the overuse of telecommunication, transportation, wildlife, and global climate resources (Diekert, 2012; Saha and Sen, 2003; Ostrom, 1999; Turner, 1992). In the transportation setting, commons constraint problems occur when users of a road network seek to maximize their expected individual utility without regard for capacity limitations (Saha and Sen, 2003). The resulting costs of congestion and pollution are felt by everyone. Klein et al. (2018) have recently introduced the term *social mobility dilemma* to emphasize the specific challenges faced by transport engineers and urban planners tasked with curbing excessive personal vehicle use on limited road networks.

Economic incentives and behavior change strategies aimed at encouraging socially cooperative alternatives to driving alone often require an accounting of the marginal external costs (MECs) of transport on the environment. An *externality* is defined as an experienced cost or benefit due to the failure of a rational economic actor to take into account the consequences of their behavior on others (Verhoef, 1994; Rothengatter, 1994). Externalities can be characterized as *positive* or *negative* depending on whether they benefit or harm parties external to the action in question.[1]

Transportation externalities may exhibit significant spatiotemporal variability, requiring policy planners to carefully delineate the affected population (Mayeres et al., 1996; Parry et al., 2007; Delucchi, 2000). For example, the cost of noise pollution due to transport may be indirectly quantified by observing the relationship between housing prices and traffic flow rates and proximity to motorways (Mayeres et al., 1996; Subramani et al., 2012). In contrast, the CO_2 emissions from the exhaust of a fossil-fuel powered automobile contribute to global climate change, which has a more diffuse, long-term marginal social cost (MSC) (Small and Kazimi, 1995). External costs need not be directly monetary in nature. For example, reductions in social welfare due to regularly congested road networks may be quantified according to the value that commuters place on travel time (VOT) (Small, 2012). An independent measure of the desire for reliable commute times (value of travel time variability, VTTV) can measure the impact of more sporadic events such as adverse weather conditions on social welfare (Coulombel and de Palma, 2014).

Reducing externalities by requiring individuals to compensate for the costs that their actions impose on others is known as *internalization. Pigouvian mechanisms* are market-based approaches that attempt to internalize externalities by taxing goods resulting in net disbenefits or subsidizing goods that result in net benefits (Pigou, 1920). However, as the spatial scope of external effects increases, Pigouvian schemes become more politically contentious, since attributing effects to their sources becomes less precise. Pigouvian mechanisms also fail to take advantage of the social effects that often shape individual behavior and preferences.

Game theoretic models of externalities assume that, at user equilibrium, individuals lack the incentive to take actions that improve social welfare if they believe that others will profit from their efforts without making a similar sacrifice in utility (Eriksson et al., 2006). However, in many cities, a growing concern over the contribution of fossil fuel emissions to climate change and increasing access to low-cost, alternative-energy transportation modes, has resulted in commuters switching to public transit, electric vehicles, and ridesharing services at rising rates (Biel and Thøgersen, 2007; SFCTA, 2010). For example, recent work studying automobile purchase decisions shows to what extent adoption of a new technology (such as electric vehicles) is driven by the spread of attitudes and behaviors (e.g., pro-environmental mode choice) as they become social norms (Gaker et al., 2011).

Traditional, consequentialist views of travel behavior have failed to explain these preferences, inspiring modern studies of transportation behavior to investigate bounded rationality, observer bias, and, increasingly, the impact of social influence on human reasoning (Grabowicz et al., 2014; Verplanken et al., 0000; Axhausen, 2007; Páez et al., 2008; Abou-Zeid et al., 2013; El Zarwi et al., 2017). Complicating claims of causality made by these experiments is the difficulty in accounting for endogeneity in explanatory variables (Dugundji and Walker, 2005). Distinguishing social influence from homophily, which is defined as the tendency for individuals with similar characteristics and behaviors to form clusters in social networks is currently a growing area of research and debate.[2]

In contrast to the passive processes governing diffusion of social influence, individuals can, at some cost in utility to themselves, actively influence each others' choices through *peer pressure* (Pentland and Reid, 2013; Calvó-Armengol and Jackson, 2010; Mani et al., 2013). In particular, when one person's choices result in visible negative externalities for his community, his peers may

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[1] The reader is referred to Mas-Collel and Green (1995) for more detail and background on the concepts from neoclassical game theory used in this text. Shoham and Leyton-Brown (2008) is also a good reference with particular emphasis on the use of game theory in multiagent systems.

[2] See Christakis and Fowler (2013) and Shalizi and Thomas (2011) for a recent exploration of the *identification problem* in the econometric analysis of diffusive processes in social networks, as first characterized in Manski (1993).

collectively decide to persuade him to make decisions that internalize the consequences of his actions, thus incrementally reducing local perception of the "free-rider" problem (Lazaer and Kandel, 1992).

While pressure is always costly to the pressuring party, it can either lower or raise the cost of pressured agents' action depending on whether it is positive or negative, respectively. A group of friends protesting a mutual acquaintance's decision to buy a fuel-inefficient SUV can be seen as negative peer pressure. On the other hand, lending a friend a bicycle for "Bike to Work" day can be seen as positive peer pressure.

Mani et al. (2013) recently developed a two-stage game theoretic mechanism that models localizing the perception of global externalities within social networks in order to drive peer pressure-induced cooperation. In this work, we adapt a similar game theoretic mechanism to a transportation setting wherein we show that peer pressure helps to internalize global externalities arising from the use of personal vehicles on road networks. Experimental evidence from validation studies based on the theory developed in Mani et al. (2013) suggests that rewarding individuals with a low cost of peer pressure amplifies the effects of subsidies by taking advantage of inherent *social capital*. These effects were shown to be more cost-effective than comparable Pigouvian internalization mechanisms.

The model of peer pressure presented herein is implemented within an agent-based microsimulation of mobility within the activity-based travel demand framework (Bowman, 1998). Activity-based travel demand models primarily differ from traditional travel demand models in that they take into account travelers' daily schedules and activity priorities (Castiglione et al., 2014). Agent-based microsimulations execute the planned activities and transportation choices of many software agents interacting on a virtual representation of physical road networks. The spatiotemporal granularity of human environments and interpersonal dynamics represented by these simulations permits the resolution of feedback loops and constraints that operate between trips purposes, travel mode alternative availability, and infrastructure status. Individual decision-making may also be made dependent on demographics such as household member composition, income, and ethnicity (Vij and Walker, 2013).

Related research efforts have incorporated the effect of social influence on transportation, particularly in the sphere of joint decision-making (Hackney and Axhausen, 2006). Studies designed to employ synthetic social networks of travelers as well as simulate joint activity choice, vehicle sharing, and household-level coordination of plans have been implemented (Dubernet and Axhausen, 2013; Illenberger, 2012). While our work is similar in that we extend a microsimulation with a social network of traveling agents, the scenario presented herein does not explicitly involve joint decision-making by agents during the course of plan evaluation.

As a tool for economic analysis of policy interventions, the agent-based approach has proven to be adaptable to modeling the effects of emissions and congestion internalization strategies (Kickhöfer and Kern, 2015; Agarwal et al., 2015; Kaddoura et al., 2015). While some of these studies investigated changes in the demand for competing modes in the presence of externalities, in contrast to the present work, they did not involve detailed public transit simulation. By modeling public transit modes that interact with passenger cars on the physical network representation, we more accurately simulate complex congestion dynamics resulting from mode shift decisions.

Policy mechanisms involving directly charging an agent with the social costs that he or she was responsible for have been evaluated by Kickhöfer and Nagel (2013) and Kaddoura et al. (2015). While effective in theory, and demonstrable in simulation, public support for congestion or emissions pricing remains lukewarm (Hårsman and Quigley, 2010; Eriksson et al., 2006). Equity may also be a concern, as users with lower incomes may feel the effects of a toll disproportionately to more affluent users (Viegas, 2001; Walter and Suter, 2003). Furthermore, it is difficult to allocate revenues from greenhouse gas emissions costs, as their social costs may extend well beyond the major metropolitan areas considered for policy changes (Verhoef, 1994). As an alternative more in line with the sentiment that global problems can benefit from local actions, the current work demonstrates how an agent can exploit his social connectivity and the slack in his daily schedule in order to secure access to the travel modality that maximizes both his personal as well as societal benefits.

3. Methodology

In this section, we present our formal model of strategic peer pressure behavior, which we have adapted from the original formulation by Mani et al. (2013) to take place within the larger context of an activity-based model of urban travel. As has already been well-established in the transportation modeling literature, the demand for travel is derived from an agent's need or desire to participate in activities (e.g., shopping or working) (Bowman, 1998; Hägerstrand, 1970). Scheduling a daily activity-travel plan requires individual agents to make several hierarchically-structured decisions that satisfy spatiotemporal constraints, financial restrictions, professional obligations, and meet a variety of other considerations.

Herein, however, we narrow the scope of this complex decision-making process to focus on the impact that active interpersonal influence has on an agent's travel mode choice in the presence of system-wide externalities arising from the concurrent execution of all agent's plans on the physical network. In the present scenario, agents are made aware of externalities such as traffic and CO_2 emissions via penalties to the utility of their realized plans. In response, agents producing the fewest externalities (e.g., public transit users) may choose to exert pressure on their peers (e.g., agents who drive alone) in the hope that they will follow suit. It is expected that daily travel mode choices will vary for individual agents as they induce and respond to peer pressure. However, if localized changes coalesce into cascading network effects and, consequently, a sufficient reduction in externalities is achieved, we expect that, at system equilibrium, individual shifts towards socially cooperative modes will be *sustained* in the form of significant increases in socially cooperative *mobility lifestyles*.

The rest of this section is organized as follows. In Section 3.1 we define the baseline model as a single agent decision problem; albeit one solved simultaneously by many agents connected via a social network. We then describe how, in the presence of multiple

Table 1
Notation summary.

N	Set of agents
$Nbr(i)$	Set of neighbors for agent i
$\mathscr{X}$	Set of accumulated plans
X	Plan memory
$\mathscr{H}$	Plan history
x^m	Daily activity-travel plan m
$\boldsymbol{a}^m$	Vector of attributes for plan m
β^m	Coefficient weights
V^m	Systematic utility function
$\boldsymbol{x}$	Action profile (set of plans for all agents)
$\boldsymbol{x}_{-i}$	Set of plans for all agents other than i
$\boldsymbol{x}^*$	Equilibrium action profile
$\boldsymbol{x}^\circ$	Action profile optimizing social welfare
ν	Externality function
mode	Mode choice indicator function
U^m	Utility function of plan m
ΔU_i	Utility gap for agent i
$\mathscr{S}$	Social welfare function
$\boldsymbol{P}$	Peer pressure matrix

agents–each attempting to make optimal decisions–we reformulate the baseline model as a two stage game. In Section 3.2, we incorporate the effect of peer pressure and describe its effect on agent behavioral preferences. To aid in comprehension, Section 3.3 presents a toy numeric example. Finally, in Section 3.4 we describe the details of a full-scale implementation of our modeling framework in the multiagent travel microsimulation. A summary of notation used in this section and throughout this article is provided as Table 1.

3.1. Baseline model

Agent decision-making behavior may be modeled as a repeated game played sequentially on consecutive days, $t = (1,2,...)$, by a set of agents $N = \{1,...,n\}$. Agents are interconnected via a social network G= (N,E), where $E \subseteq N \times N$. Each agent, $i \in N$, has at most K peers in their neighborhood, $Nbr(i) = \{j: (i,j) \in E\}$, such that the graph representing the social network is sparse. An ordered pair of vertices $(i,j) \in E$ denotes a directed social tie emanating from i and incident upon another agent j; conversely, the pair $(j,i) \in E$ denotes a directed edge from j to i. In our formalism, the meaning of edges starting and terminating at the same vertex is undefined, so $E = \{(i,j) \in 2^N | (i \neq j)\}$. The social network structure is assumed to be static: links between agents are fixed and link formation and destruction processes are undefined. For simplicity, ties are assumed to be reciprocal in strength.

At the beginning of each day t each agent $i \in N$ chooses a single activity-travel plan x_{it}^m from a finite individual set of accumulated plans $\mathscr{X}_{it}$. The selected plan x_{it}^m represents a *mental model* of i's schedule on day t, which execute in a *physical model* of the network environment. More specifically, the physical model simulates the spatiotemporal dynamics of daily interactions between agents' vehicles on a capacity-constrained transportation network that permits travel between activity facilities at times specified by the schedule. The full history of an agent's executed plans is denoted $\mathscr{H}_i$.

A vector of plans, which we term an *action profile* $\boldsymbol{x}_t$ represents the outcome of the plan selection process for all N agents. The action profile indicates which plans to *simultaneously* execute in the physical layer. Once a plan has been executed, an agent may choose to modify the plan based on beliefs of future system performance, which themselves are updated conditional on information gathered from their past experiences. Due to the competition of agents for finite road access, subway car space, and other transportation infrastructure capacity constraints, the quality of an agent's plan depends on the decisions $\boldsymbol{x}_{-it}$ of the $N \backslash \{i\}$ other agents, which we denote $-i$. In order to better capture constraints on human abilities to remember and adapt to the specifics of their daily travel experiences in a dynamic, multi-agent urban environment, agents occasionally forget plans that they rarely execute.[3] An agent i's *memory* X_i, is a fixed size vector, containing tuples of previously experienced plans, $x_{it}^m \in \mathscr{H}_i$ and a corresponding utility score U_{it}^m. A *removal rule* is associated with each X_i, which ensures that agents maintain bounds on the cardinality of X_i, i.e., $|X_i| = M$ at any time t.

The solution concept for the physical system is, in this case, an agent-based stochastic user equilibrium (SUE) (Flötteröd and Kickhöfer, 2016). Let $\boldsymbol{x}^*$ denote the steady-state action profile that is consistently selected and executed at equilibrium. Once SUE is achieved, for all t, each agent is assumed to select plans, x_i^m from a fixed memory, X_i^*, that maximize his enjoyment of activities while minimizing other marginal private costs (MPC) associated with scheduling choice dimensions such as travel mode, route, activity destination and departure time. These attributes are represented as a vector, $\boldsymbol{a}_{it}^m$. Once x_{it}^m is selected and executed, the total utility that i derives from the plan over the course of day t is partially governed by a *systematic utility* function, $V_{it}^m = V(\boldsymbol{a}_{it}^m) \ \forall \ m$. The

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[3] The agents may thus be said to possess *imperfect recall* due to their limited memory (Rubinstein, 1998). Relaxing the strict informational requirements of perfect recall also has beneficial computational implications, since maintaining the experienced plan histories for all n players would be computationally infeasible (Waugh et al., 2008).

systematic utility of a single plan for agent i is a linearly-weighted combination of attributes for the plan:

$$V_{it}^m = \beta_{it}^{m\top} \boldsymbol{a}_{it}^m, \tag{1}$$

where β_{it}^m is a vector that parameterizes the marginal utility of plan x_{it}^m's attributes. At SUE, agents are generally fully conscious of the attributes governing their own choice of optimal plan, although they may only be vaguely aware of the attributes governing other agents' choice of plan.

Assuming that the random errors for agents associated with selection of plans at SUE are independently, identically distributed type I extreme value, the plan selection probabilities in the baseline model are assumed to be specified by a multinomial logit discrete choice model,

$$P(x_{it}^m | X_{it}) = \frac{e^{\mu_i U_{it}^m}}{\sum_{U_{it}^k \in X_{it}} e^{\mu_i U_{it}^k}}, \tag{2}$$

where μ_i is a heterogeneous scale factor measuring the agent's preference for higher scoring plans serving as a rationality parameter, where $\mu \to \infty$ corresponds to a deterministic choice of the best performing plan. This assumption corresponds to the standard random utility model (Train, 2009; Ortúzar and Willumsen, 2011).

When planning his day, an agent typically ignores the marginal external costs (MEC) that execution of their preferred plan in the physical environment imposes on other agents. In order to account for agent preferences in the presence of aggregate external costs, we introduce an externality function, $\nu_{it}: \boldsymbol{x}_{-it} \to \mathbb{R}$ representing the disutility experienced by i due to $\boldsymbol{x}_{-it}$. The total utility of plan selection for agent i on day t is then defined as:

$$U_{it}^m(x_{it}^m, \boldsymbol{x}_{-it}) := V_{it}^m - \nu_{it}(\boldsymbol{x}_{-it}). \tag{3}$$

In order to lighten notation, we drop further indexing on t and m. The sequential nature of simulation and memory effects are highlighted wherever it is germane.

In the physical model, agents travel between activities by either driving a car or by using some more socially cooperative form of transportation (*e.g.*, public transit or walking). At equilibrium, every agent is assumed to have a preferred choice of transportation mode corresponding to the plan $x_i \in X_i^*$ with maximum U_i. We denote $\text{mode}_i(X_i^*) \in \{\text{car,sc}\}$ as the preferred transportation mode for a single agent at SUE. A driving agent is an agent for whom $\text{mode}_i(X_i^*) = \text{car}$, and, likewise, an agent that prefers to commute using socially cooperative modes of transportation has $\text{mode}_i(X_i^*) = \text{sc}$. While agents may have forgotten the details of previously selected plans when considering a change in the choice of transportation mode used during daily travel, they do remember the utility associated with their best past experience of the different modes used during plan execution.[4]

An agent is also assumed to be generally aware of the primary transportation mode that his neighbors $j \in Nbr(i)$ prefer to use. We define $\Delta U_i = \Delta U_i(X_i)$ as the *utility gap*, which expresses the difference between the utility score of i's equilibrium plan and the utility of the best scoring socially cooperative (*i.e.*, transit or walking) plan in i's memory, which we denote

$$x^\circ_{i,\text{sc}} := \underset{(x_i) \in \{\boldsymbol{x} | x_i \in X_i^*; \text{mode}(x_i) = \text{sc}\}}{\text{argmax}} U_i(x_i, \boldsymbol{x}_{-i}).$$

The social welfare is defined as the sum of utilities experienced by all agents following plan execution:

$$\mathscr{S}(\boldsymbol{x}) := \sum_{i \in N} U_i(x_i, \boldsymbol{x}_{-i}). \tag{4}$$

The action profile optimizing social welfare is denoted $\boldsymbol{x}^\circ$. In the presence of externalities, we know that the social welfare at the equilibrium action profile, $\boldsymbol{x}^*$ is suboptimal, since marginal social costs (defined as the sum of MECs and MPCs) no longer reflect an agent's *willingness to pay* (Verhoef, 1994). Therefore, at equilibrium $S(\boldsymbol{x}^*) < S(\boldsymbol{x}^\circ)$.

3.2. Modeling peer pressure

By allowing agents to engage in peer pressure, the social costs implicit in the production of externalities can be internalized, bringing the social welfare of our model of the transportation system economy closer to the optimal value. We introduce peer pressure into our model as follows.

Let the matrix $\boldsymbol{P} \in \mathbb{R}_+^{n \times n}$ denote the peer pressure profile, consisting of elements P_{ij} indicating the pressure that i exerts on peer j. The transpose of this matrix, $\boldsymbol{P}^\top$, consists of elements P_{ji}, representing agent j's pressure on i. If $j \neg \in Nbr(i)$, then $P_{ij} = 0$.

The utility function with peer pressure is

$$U_i(x_i, \boldsymbol{x}_{-i}, \boldsymbol{P}) = V_i(x_i) - \nu_{it}(\boldsymbol{x}_{-it}) - \sum_{j \in Nbr(i)} P_{ji} - c \sum_{j \in Nbr(i)} P_{ij}, \tag{5}$$

where the third term is the cost applied if i is pressured, while the fourth term is applied to the utility function as a sum of the costs accrued for i pressuring other eligible peers in his immediate social network. The *marginal cost of peer pressure* for each agent is c utils per unit of pressure. This parameter is indicative of the ease or difficulty with which one agent may pressure another agent. While in

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[4] This specification is made in accordance with empirical research in behavioral economics on peak-end bias (Fredrickson and Kahneman, 1993; Carrel et al., 2013).

this study c is specified to be constant and homogeneous across the population, an agent-specific marginal cost of peer pressure can be considered in future work.

Agent-specific pressure selection strategies initially specify which agents may pressure each other. These strategies may be composed. We specify two such strategies below, followed by a detailed presentation of the peer pressure profile selection algorithms in Section 3.4.3.

For the first strategy, we specify that an agent who uses public transit or some other socially cooperative mode can pressure any peer in her neighborhood who drives. For any agent i whose equilibrium mode choice, $\text{mode}_i(X_i^*) = \text{car}$, any peer $j \in \{k \in Nbr(i) | \text{mode}_k(x_k^*) = \text{sc}\}$ is permitted to pressure i to consider using an alternative to driving. Thus, in this strategy, peer pressure on i can only take effect if

$$\sum_{j \in Nbr(i)} P_{ji} \geqslant \Delta U_i = U_i(x_i^*, \boldsymbol{x}_{-i}) - U_i(x^\circ_{i,\text{sc}}, \boldsymbol{x}_{-i}). \tag{6}$$

Implicit in this criterion is a measure of accessibility to driving alternatives. Thus, people who do not retain a memory of public transit use at SUE would automatically be excluded from being pressured, as it would be too costly for any peer or group of peers to pressure them.

As a further strategy, we specify that an agent i who drives and has a utility gap greater than any agent $j \in \{k \in Nbr(i) | \text{mode}_k(x_k^*) = \text{car}\}$'s utility gap, $\Delta U_i > \Delta U_j$, can pressure j. This predicate measures the extent to which captive drivers would pressure other drivers with access to alternative commute modes to shift off driving in order to potentially benefit from reduced congestion.

3.3. Example

We now present a numeric example that walks the reader through the computations performed during a round of the peer pressure game set in a fictitious travel environment. For simplicity, we will assume that units of utility are represented as *utils*. Consider a 'society' of three roommates (Fig. 1), represented by agent i, j, and k, who commute to the same job (i.e., they all have the same home and work facility locations). We assume that each person derives an identical total utility of 100 utils from their daily activity schedule. Agents i and k typically commute via a municipal metro rail line. These two agents suffer from the greenhouse gas contributions of a mutual friend, agent j, who prefers driving an SUV to work over taking the train by $\Delta U_j(\boldsymbol{x}_0) = 20$ utils. Agent j's action results in a 14 utils disutility due to CO_2 emissions, which is felt by i and k equally. As public transit riders, i and k do not produce externality through their respective actions. The net social welfare in this situation is $\mathscr{S}(\boldsymbol{x}) = 100 + 86 + 86 = 272$ utils.

Now, suppose that agents i and k both pressure agent j to leave his SUV in his garage and join them on the train such that $P_{ij} + P_{kj} \geqslant \Delta U_j = 20$ utils, as indicated in Eq. (6). In this scenario agent i does not know that agent k will pressure j and vice versa such that each applies 20 utils of pressure for a total of 40 utils of pressure applied to j. Assuming that the marginal cost of pressure, c is 0.05 utils/unit pressure, the cost to pressure agent j for agents i and k is $c\Delta U_j = 1$ utils each. Agent j then avoids the inconvenience of the 40 utils of peer pressure that he would otherwise lose by indicating that he will join agents i and k on the train in the near future. The initial cost of pressure together with j's disutility for taking the train amounts to a social welfare loss of 22 utils, which is balanced by a social welfare improvement of 28 utils due to reduced externalities, resulting in a net social welfare gain of 6 utils.

3.4. Implementation overview

In order to implement the peer pressure game in a setting that allows for its economic evaluation in large, disaggregated urban transportation environments, we extend an existing open source activity-based travel microsimulation platform, MATSim (Horni et al., 2016). This subsection briefly outlines the simulation runtime cycle, the operation of the congestion and emission externality modules, as well as the implementation of the peer pressure extension developed for this work. Scenario evaluation with peer pressure differs significantly from the state-of-the-art use of MATSim-based tools and is described below in detail.

3.4.1. Simulation platform

The core MATSim system is an open source development effort that facilitates demand modeling, dynamic traffic assignment,
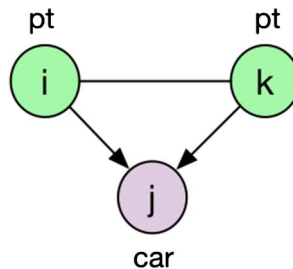

Fig. 1. Example social network of three agents i, j and k. Agents i and k currently commute via public transit and wish to pressure j, who currently drives to work, to also take public transit.

mobility simulation, and analysis. Several extension modules provide additional functionality applicable to modeling a variety of policy analysis scenarios. The extant MATSim API, employed extensions, and software developed as part of the current study are written in Java with associated analysis scripts developed in Python. We have developed our tool as an open-source module extending the main MATSim library (GPL Version 3)[5]

Every scenario simulation execution proceeds in an iterative manner according to the following four steps:

1. **Preparation.** During a single iteration, a simulated population of agents execute plans representing the typical daily home-based work tours. Plan elements consist of activities alternating with travel legs that describe the routes taken between activities. The activities have attributes of type (*e.g.,* home, work, leisure, etc.), location, start time, and duration, while the trip legs have attributes of mode, departure time, distance, as well as elements describing the traversal of routes through the network (*e.g.,* links used, type of links, and total distance traveled). If a population's initial plans are not available with fully detailed routes, one of the several available shortest path algorithms is used to calculate initial idealized daily trajectories.

2. **Mobility Simulation.** Following initial route assignment, the daily plans of the agent population are executed in the physical layer, which is represented by the links and nodes comprising the virtual road network topology. Public transit supply for modes such as subway or train are modeled on links and nodes that route vehicles separately from the road network (Rieser, 2010), while buses share the links with general traffic unless a dedicated transit lane is available.

3. **Scoring.** Agents have a configurable memory that permits them to choose between previously executed plans. In order for agents to simulate decision-making that models human behavior, an econometric utility function assigns a numeric score to executed plans (Charypar and Nagel, 2005; Horni et al., 2016). Specifically, for agent i a plan, x_i^m, once executed, is assigned a score U_i^m, according to the time spent performing activities and the time spent traveling to and from activities:

$$U_i^m = \sum_{q=0}^{A-1} U_{\text{perf},q} + \sum_{q=0}^{A-1} U_{\text{trav,mode}(q)}, \tag{7}$$

where A is the number of activities and trip q follows activity q, as described in Horni et al. (2016). In order to represent a typical 24-h period, the first and last activity are considered in the same iteration such that there are the same number of trips and activities.

The utility earned due to time spent engaging in activities, $U_{\text{act},q}$, is primarily a function of the time spent performing the activity $\tau_{\text{act},q}$:

$$U_{\text{act},q}(\tau_{\text{act},q}) = \beta_{\text{act}} \tau_{\text{typ},q} \ln\left(\frac{\tau_{\text{act},q}}{\tau_{0,q}}\right), \tag{8}$$

where β_{act} denotes the marginal utility of performing an activity for its typical duration, τ_{typ}. At equilibrium, β_{act} is the same for all activities and is equivalent in magnitude to the penalty applied to being late to an activity. The parameter $\tau_{0,q}$ scales the actual time spent performing the activity $\tau_{\text{act},q}$ by the activity's priority and minimum duration, and may be ignored as long as dropping activities is not permitted.

Agents also receive a penalty for arriving late at an activity according to

$$U_{\text{late},q} = \begin{cases} \beta_{\text{late}}(t_{\text{start},q} - t_{\text{latest ar},q}) & \text{if } t_{\text{start},q} > t_{\text{latest ar}}, \\ 0 & \text{otherwise} \end{cases}$$

where $t_{\text{start},q}$ specifies the start time of activity q, $t_{\text{latest ar}}$ specifies the latest possible time that an agent can arrive at activity q.

Travel in the MATSim physical environment is associated with a utility penalty, which varies according to trip cost, the mode-specific perception of trip travel time, and, potentially, several other factors. To simplify model calibration, we include only the mode-specific cost associated with travel time in the structural equations. The drive-alone mode-related parameters are subscripted with car and the alternative public transit mode is subscripted with pt. While walk-to-transit and walking modes are included in the simulation, they are not detailed here to simplify the notation.

Travel-related utility scores are computed according to the following expressions

$$U_{\text{car},q} = \beta_{\tau,\text{car}} \tau_{q,\text{car}} \tag{9}$$

$$U_{\text{pt},q} = \beta_{0,\text{pt}} + \beta_{\tau,\text{pt}} \tau_{q,\text{pt}}, \tag{10}$$

which are linear in the alternative-specific time parameters, $\beta_{\tau,\text{mode}(q)}$. In accordance with random utility theory, the β_0 terms are alternative-specific constants (ASCs) that characterize other factors that systematically predispose individuals to choose one alternative over another (Train, 2009; Ben-Akiva and Lerman, 1985).

4. **Replanning.** Following scoring, the most recently executed plan is stored with a configurable number M of previously executed plans, X_i in system memory. At the beginning of the subsequent iteration, agents choose a new plan based on a configurable selection module and an optional route modification module. In this study, innovative modification strategies include: changing

---

[5] Code to reproduce the simulation and analysis presented in this study is available at http://github.com/sfwatergit/peer_pressure_sim.

the departure time, link sequence (route), and choice of transit-related modes including legs performed by walking. While the default configuration specifies that agents select their current best score for modification, we opt to use a probabilistic sampling strategy to achieve a more realistic distribution of agent plans for selection, as given by Eq. (2). The plan with the worst score is then dropped from the agent's memory, and the modified plans are simulated again.

Steps 2–4 are repeated until a stochastic user equilibrium is reached. Please note that the iterative cycle of replanning should not be interpreted as representing a day-to-day dynamic model of human learning behavior. It may only be assumed that consecutive iterations bring the system closer to an equilibrium point. For further discussion on this topic, see (Horni et al., 2016).

3.4.2. Computing and applying externalities

Once a baseline calibrated scenario has been derived, the travel behavior of the study population is permitted to evolve in the presence of externalities. That is, the simulation steps described in Section 3.4.1 are repeated except that agents are made aware of the effects of congestion and emissions due to the decision of other agents to drive. Herein, as described in Section 3.1, we assume external costs are globally distributed, and are consequently applied as in Eq. (3).

The following paragraphs briefly review design choices used in this study to simulate agent air emission and congestion externalities. The adopted methodology is derived from Agarwal et al. (2015) that studies the shift from private to public transit due to emissions and congestion pricing.

Emissions. Costs associated with air pollution due to emission of combustion gases during driving activities are computed following the work of Kickhöfer and Nagel (2013). Emissions calculations are performed on a link-by-link basis, tying attributes of a traveler's vehicle and road conditions to air pollution parameters. Since road type and quality affect pollutant levels, initial routing computations are modified to anticipate this additional cost, such that agents may choose to travel on roads that avoid creating excess emissions.

Herein, as opposed to earlier work using this module, we consider CO_2 production only. This study investigates the effects of externalities that result in a more diffuse social cost, and, therefore, are more difficult to internalize through regulation. Other automobile exhaust constituents do, indeed, result in transportation externalities, however we restrict the computations to arguably the most representative one for simplicity. Accordingly, we focus on the global warming potential (GWP) of CO_2, and do not simulate the damages due to other emissions.

Congestion. Road network congestion is computed as in Kaddoura et al. (2015) by taking advantage of the queue model that underlies the traffic flow simulation. In free flow conditions, agents take τ_{free} to traverse a link. A maximum of c_{flow} agents may leave a link in a given time span. Any link traversal by an agent prevents following agents from accessing the next link until $\frac{1}{c_{flow}}$ has passed, resulting in delays, d_{flow}. Spill-back delays ($d_{storage}$) may also arise if the storage capacity $c_{storage}$ of a link, measured in number of vehicles, is exceeded.

Delays are measured in seconds and computed as the difference between the free speed travel time (τ_{free}) and the travel time experienced by an agent (τ_{exp}):

$$d_{tot} = \tau_{free} - \tau_{act} = d_{storage} + d_{flow} \tag{11}$$

During the replanning stage, agents take into account delays due to congestion accrued in the previous iteration, potentially motivating less congested routes or mode shift.

3.4.3. Simulating peer pressure

The eligibility of agents to participate in the peer pressure distribution stage is described in the methodology Section 3.2. The algorithm is outlined in Algorithm 1 with the conditions defining an agent's eligibility to pressure and be pressured provided, for clarity, as flowcharts in Fig. 2. In order to simulate the effect of peer pressure, we modify the mode change strategy to potentially reroute the just completed plan for public transit. Once members of a driving agent's social network sufficiently pressure him to consider an alternative mode, their most recently executed plan is then flagged. Flags expire after a number of iterations equal to the size of the agent's memory. Thus, if, through the plans sampling process, an agent does not choose the flagged plan by the expiration iteration, the plan will no longer be eligible for rerouting until the agent is pressured again. The expiration condition models the idea that the memory of social influence is ephemeral, and that not every attempt of pressure will be successful.

Algorithm 1. Peer Pressure Algorithm

```
for i ∈ G do
   if isEligibleToBePressured(i) then
      Ptotal[i] ← 0
      for j ∈ Nbr(i) do
         if isEligibleToPressure(j) then
            Ptotal[i] ← Ptotal[i] + ΔUᵢ
         end if
      end for
      if Ptotal[i] ⩾ ΔUᵢ then
         Uᵢ ← Uᵢ − ΔUᵢ
```
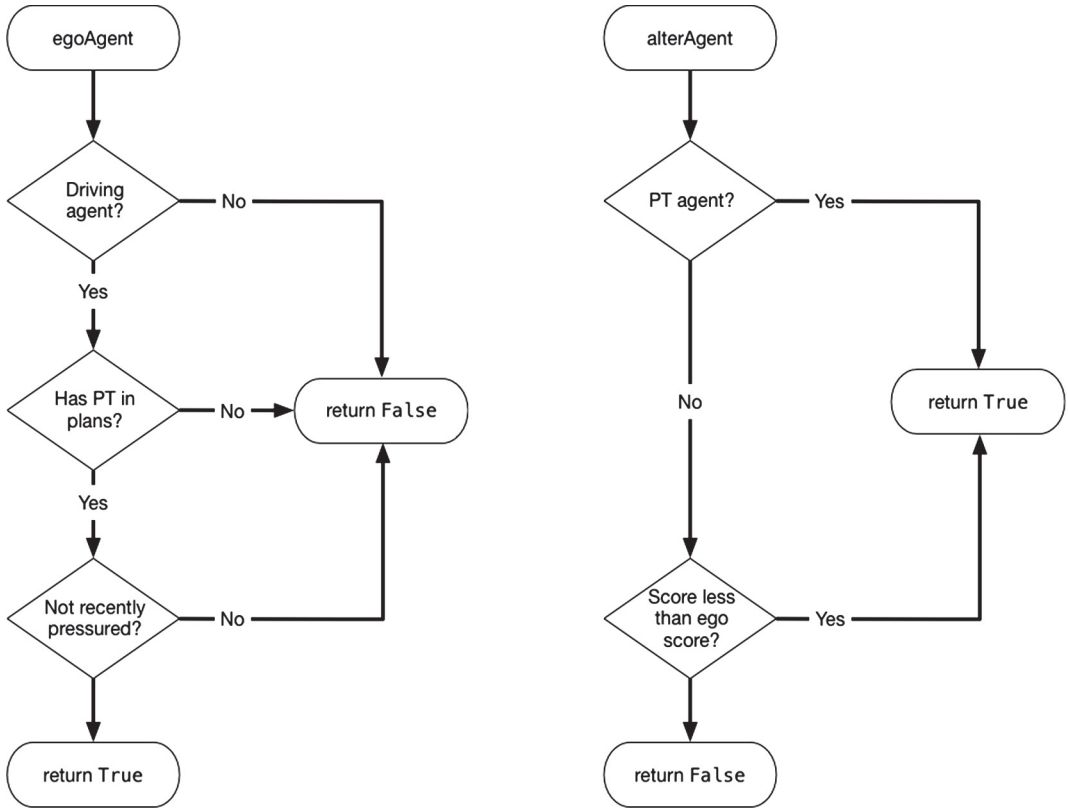
(a) Agent eligibility to be pressured   (b) Agent eligibility to apply pressure

Fig. 2. Pressure decision-making flowcharts: agents eligibility to participate in peer pressure distribution.

$\quad\quad$ flag(x_i^*)
$\quad\quad$ **end if**
$\quad\quad$ **for** $j \in Nbr(i)$ **do**
$\quad\quad\quad$ **if** isEligibleToPressure (j) **then**
$\quad\quad\quad\quad$ $U_j \leftarrow U_j - c\Delta U_i$
$\quad\quad\quad$ **end if**
$\quad\quad$ **end for**
$\quad$ **end if**
end for

4. Case study

In order to verify the functionality of the peer pressure algorithm on a large scale travel demand scenario, we have applied the framework described in Section 3 to a simulation of San Francisco Bay Area daily commute traffic.

4.1. Simulation data sources

4.1.1. Network
The road network, consisting of 96,000 links, and representing freeways, state routes, all major arterials, and countryside roads, was generated from Open Street Map data.

We use a fully integrated public transit routing module (Rieser, 2010), permitting a highly detailed simulation of Bay Area public transit throughout the course of the day. Physical track and scheduling data for the public transit system are derived from General Transit Feed Service (GTFS) data and include 9 major transit agencies operating light rail, metro and bus routes. The initial modal split has been calibrated to passenger counts obtained from the regional transportation planning authorities, the Metropolitan Transportation Commission. See Fig. 4 for a map of the transit lines used in this study.
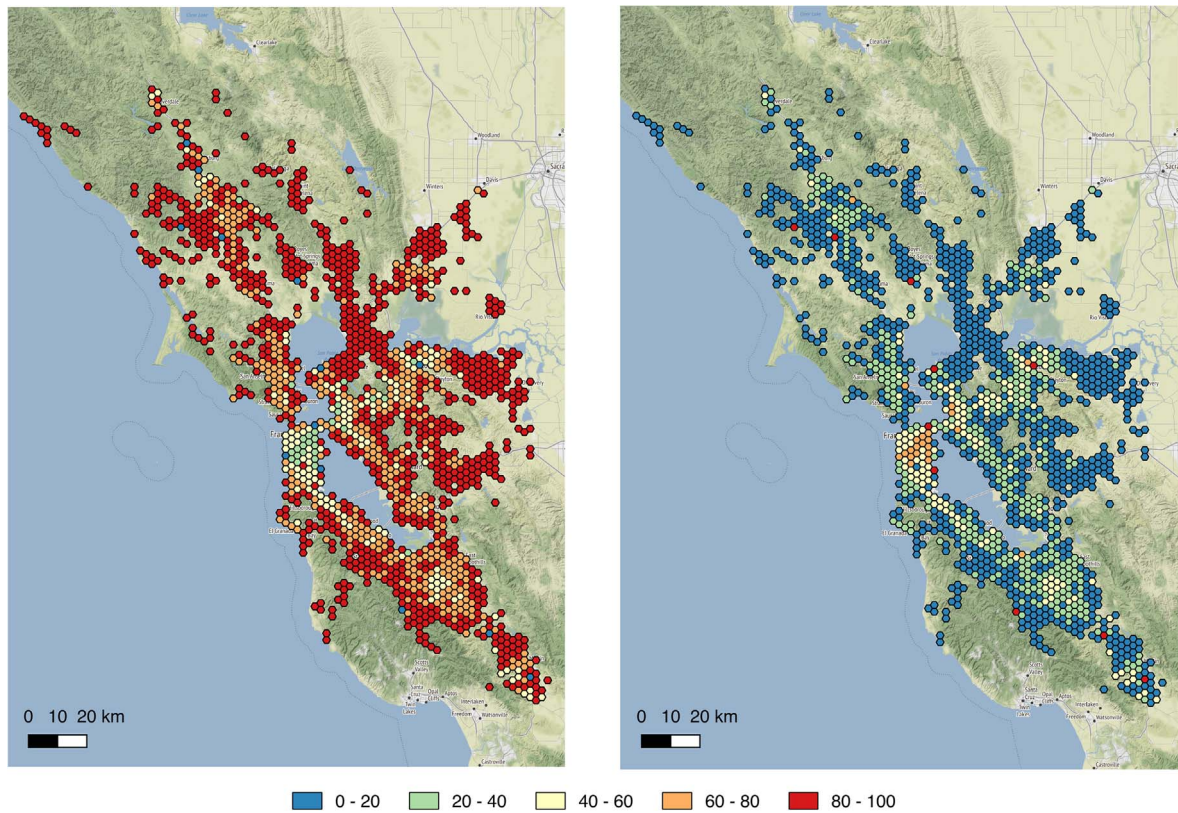
Fig. 3. Home locations, by commute mode, of the baseline agent population: percent counts of driving agents (left) and socially cooperative modes (right).

4.1.2. Initial plans

The population of the study area in 2015 was approximately 7.5 million people. Of the estimated 3.4 million commuters, 75% drive alone, while 11.5% take public transit and 3.5% walk to work. A base population of synthetic commuters, comprising 50% of the Bay Area was adopted from the Bay Area Travel Model One of the Metropolitan Transportation Commission, and adjusted with anonymized cell phone data logs. Cell phone data records (CDRs) are collected and managed by a major national carrier were recorded at the spatial resolution of cell phone towers. Home and work locations generated from these CDRs are upscaled to match the marginals of the population census, and then sampled to produce a desired number of agents in the synthetic population. A complete methodology of generating activity-based travel demand models from cellular data is described in Yin et al. (2017).

Due to the computational requirements of composing the emission, congestion, and the detailed simulation of public transit, as well as the social network and peer pressure simulation developed as part of this project, a 1% sample of the full synthetic population was used. The spatial distribution of the synthetic agents home locations split by the commute mode of the initial plan set is illustrated in Fig. 3. It is instructive to compare modal split to the layout of the transit network in Fig. 4. Recognizing the limitations of using a small sample, in practice one has to face heavy computational loads of simulating detailed behaviors of 50,000 inter-connected agents. As a result, network flow capacities for network links are scaled down to 1%. Following recommendations found in Kickhöfer and Agarwal (2015), storage capacities are scaled to 3% in order to achieve realistic congestion patterns. Rescaling did not substantially affect the attainment of validation metrics.

4.1.3. Social network generation

No individual level personally identifiable information was used in the study. A synthetic social network for the population of 50,000 agents was generated. An algorithm used to generate ties in the network respects core statistics of the network graph (node degree distribution, clustering coefficient), as well as the household composition, the marginals of the socio-demographic attributes (age, gender, income) of nodes, and the macro-level spatial patterns of the network community structure. It involves using probabilistic Bayesian networks (Sun and Erath, 2015) to match the conditional distributions of the socio-economic parameters describing the households composition, and the exponential random graph models (ERGM) (Schweinberger and Handcock, 2015) to fit the identified network statistics and community structure parameters. The complete methodology of simulating a required social network was adopted from the algorithms of Zhang et al. (2017).

4.1.4. Behavioral parameters

Behavioral parameters used in the simulation and provided in Table 2 generally match the accepted specifications described in
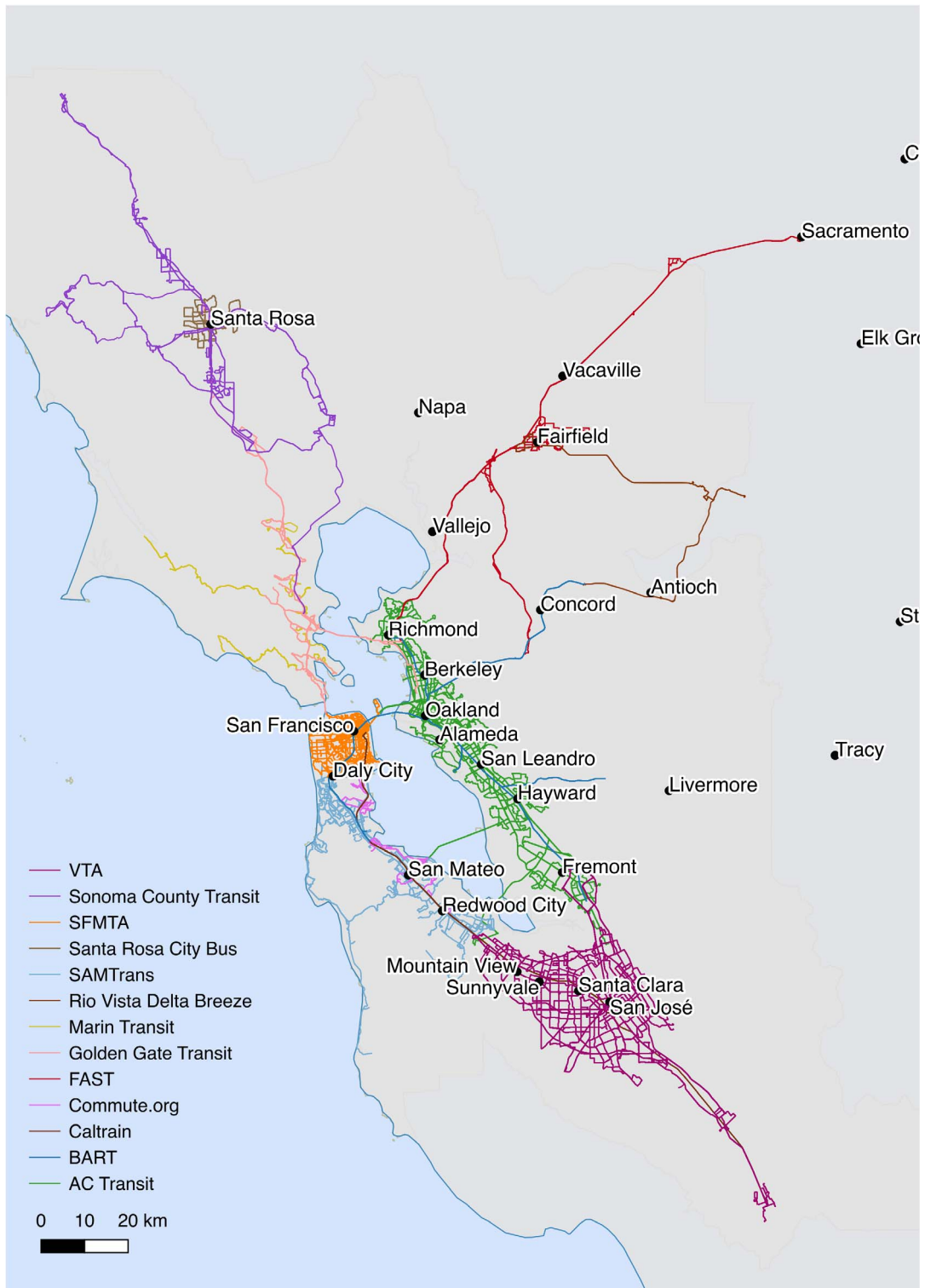
Fig. 4. Transit lines used in simulation.

Horni et al. (2016), Chapter 3, except for the values specific to the region in question. Particularly, the alternative specific constants for public transit were adapted to match the observed volumetric passenger counts. Additionally, the marginal utility of money, β_m was derived from survey data used for the San Francisco Mobility, Access, and Pricing Study (SFCTA, 2010).

Table 2
Behavioral parameters of the utility functions specification.

Parameter	Description	Value	Unit
β_{perf}	Marginal utility of performing activity	1.205	util·h^{-1}
β_{late}	Utility of late arrival	-18	util·h^{-1}
$\beta_{\tau,\text{car}}$	Marginal utility of time (car)	-0.134	util·h^{-1}
$\beta_{\tau,\text{pt}}$	Marginal utility of time (public transit)	-0.16	util·h^{-1}
$\beta_{\tau,\text{walk}}$	Marginal utility of time (walking)	-0.29	util·h^{-1}
$\beta_{\text{wait,pt}}$	Marginal utility of waiting for public transit	-0.044	util·h^{-1}
β_{ls}	Marginal utility of line switch	-0.045	util
$\beta_{0,\text{pt}}$	Alternative specific constant (public transit)	3	util
$\beta_{0,\text{walk}}$	Alternative specific constant (walking)	-1	util
β_m	Marginal utility of money	0.083	util·"\$"$^{-1}$

4.1.5. Emissions module parameters

The existing emission extension developed in Kickhöfer and Agarwal (2015) adheres to European standards, practices, and driving conditions. In order to better align with the local physical and regulatory transportation environment, the module's source code was altered to be compliant with USEPA and (when available) California Air Resource Board (CARB) emission models. Emission factors used in simulation calculations are derived from the CARB's EMFAC2014-LDA passenger vehicle model aggregates for the San Francisco Bay Area Air Quality Basin (CARB, 2014). Emission monetary costs are computed using the United States Environmental Protection Agency's Social Cost of CO_2 statistics (IAWG, 2015). These are provided at variable discount rates (1, 3, and 5%). We use the moderate \$36/tonne CO_2 derived using the 3% discount rate as a reasonably conservative measure of the social cost of carbon, noting that a value of as high as \$120/tonne may be used in particularly risk averse scenarios. As in Kickhöfer and Nagel (2013), we assume that public transit use has negligible emissions in comparison to automobile travel.

4.2. Simulation experiments

The workflow for the simulation experiments performed in this study are presented in Fig. 5. Individual steps are discussed below.

4.2.1. Baseline scenario

A calibrated base case is first established for policy comparison purposes. To derive a baseline scenario, agents are permitted to adaptively optimize their plans using the MATSim co-evolutionary algorithm described in Section 3.4. Prior to each iteration 20% of agents selected at random will have either their selected plan rerouted, trip departure/arrival times modified, or the travel mode for their daily commute will be shifted from private to public transportation. The simulation continues until the population ensemble average scores reach a stable point, which we found was approximately 200 iterations. Simulated volumetric flows on road network links are compared to data from the California DOT freeway Performance Management System (PeMS) as described in Yin et al. (2017). Simulated transit stop entry and exit data from simulated BART agents is also compared to ground truth hourly counts aggregated during October 2013.

4.2.2. Externalities equilibration

After a stable, calibrated baseline has been reached, the set of plans in agent memory are carried forward to the next part of the simulation. Agents are now allowed to modify and reroute their plans in the presence of system-wide externalities, as described in Section 3.4.2. We find that the simulation reaches a fixed point after an additional 100 iterations.

We calibrate the congestion and emission externalities using linear scaling factors of 10^{-5} and 10^{-4} respectively so that they contribute in the order of 10% of the typical agent score. While quantifying the influence of globally-distributed negative externalities as well as environmental awareness on individual decision making is largely an open research problem, in the present we follow (Agarwal et al., 2015) to set this order of magnitude.

The output plan data from the final iteration of the base model with externalities are used in welfare comparisons.

4.2.3. Peer pressure scenario

In the peer pressure experiments, utility is assigned according to Eq. (5). For each run of the policy case, the value of c (marginal cost of pressure) is set beforehand and innovative strategies are maintained as before.

Peer pressure is specified to begin after 5 iterations to verify that the start point of the run is equivalent to the base case end point. Innovative strategies are retained in order to permit agents to modify and optimize their plans in response to peer pressure. We run the simulation with pressure and innovative strategies until iteration 80, at which point plan innovation is turned off. This was done to view how the system relaxes when plans are fixed.

The algorithm used to implement peer pressure in the microsimulation context is provided in Fig. 2. Recall from Eq. (5) that the parameter, c, is the marginal cost of pressure. For all agents in a simulation run, we assume a homogeneous value of c. In the present study, all peers, $j \in Nbr(i)$ will pressure i as long as they are eligible to do so. For example, let π_i be the number of peers eligible to
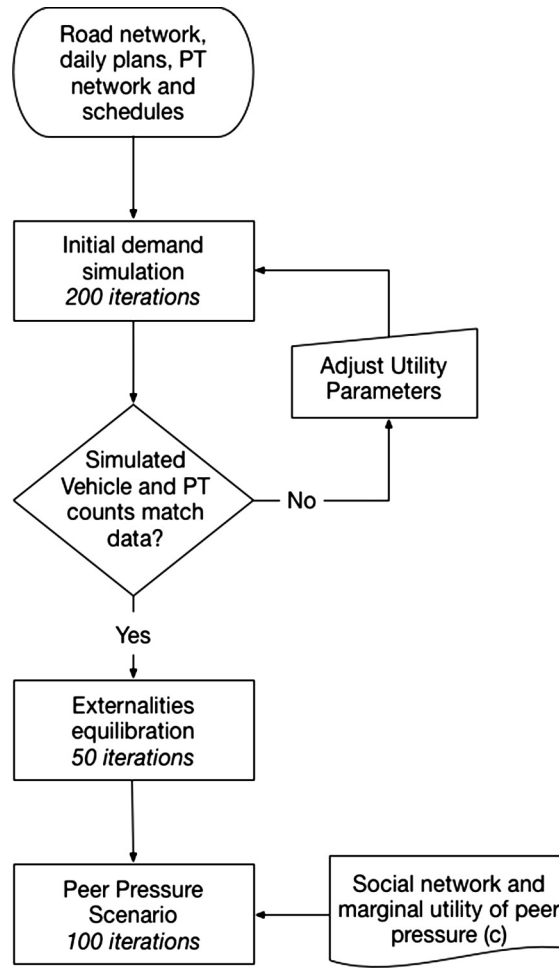
Fig. 5. Peer pressure simulation stages.

pressure an agent i under the first pressure strategy. Then, U_i will be penalized by ΔU_i utils and each $j \in \pi_i$ will be penalized $c\Delta U_i$ utils. Then, the change in social welfare for the system due to peer pressure under action profile $\boldsymbol{x}$ is given by $-\sum_{i \in N}(1 + c \cdot \pi_i)\Delta U_i$ utils.

Since empirical data on the social cost of peer pressure in this context is unavailable, we performed a sensitivity analysis by running the simulation for a range of magnitudes of c, ranging from 0.001 to 10, while holding all other parameters constant.

5. Results

5.1. Peer pressure: Effect on mode shift and system dynamics

In this section, we examine the effect of peer pressure on mode shift and score evolution as well as how system dynamics and target metrics vary with the marginal cost of peer pressure, c.

In Fig. 6, the number of agents that switch mode between iterations is plotted over time at different values of c. Clearly, for all of the values of c explored, *ceteris paribus*, peer pressure is effective in achieving attenuation in the net number of drivers. Once innovative strategies are turned off, at $t = 80$, the number of shifted agents eventually drops to 0, as expected, since, at this point, agents only select between existing plans in their plansets. Although the simulation with peer pressure was not run to convergence, we observe in Fig. 6 that the maximum number of agents shifted per iteration does appear to be reaching a fixed point.

When exploring the dynamics of the system as a function of c and $50 < t \leq 80$; however, we observe that a phase transition in the stability of system evolution may occur between $c = 0.01$ and $c = 1$. Specifically, in Fig. 6, we note that for $c = 0.001$ and for $c = 0.01$ at $t > 50$, the number of agents shifted begins to oscillate around an upward trending baseline. These oscillations are on the order of 1×10^3 agents and have a period of 10 iterations. This second order phenomenon is almost entirely absent in the simulation for values of $c \geqslant 1$.

For $c = 0.01$, Fig. 8 demonstrates that the number of agents pressured and mode share are roughly covariant. This observation suggests that oscillations in the system evolution occur due to synchronization of pressure-induced mode shift forcing and ephemeral
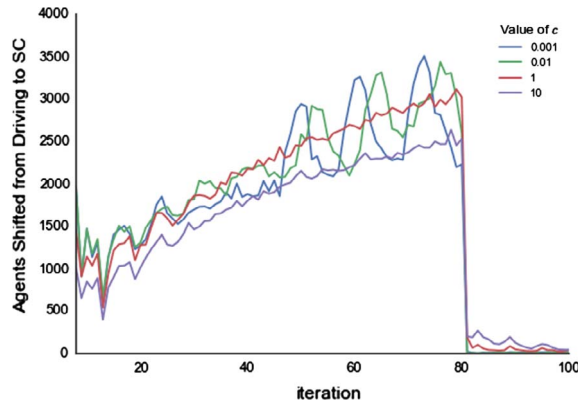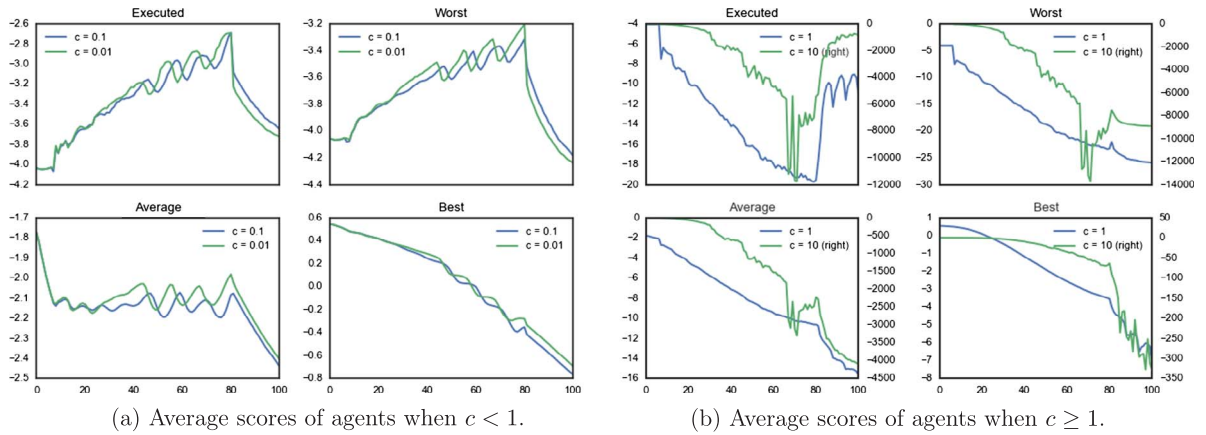
Fig. 6. Net number of agents shifting to socially cooperative modes for different values of the marginal utility of peer pressure.

(a) Average scores of agents when $c < 1$.

(b) Average scores of agents when $c \geq 1$.

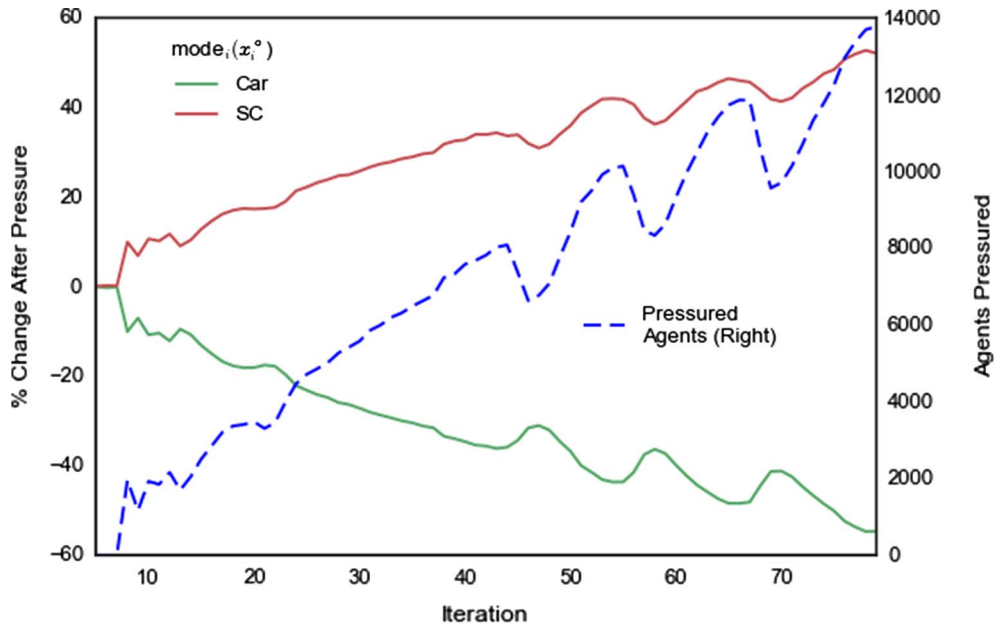**Fig. 7.** Ensemble average score sensitivity of agents to value of c. Scores are in utils.


Fig. 8. Evolution of percent changes in transportation mode share with number of agents pressured following initiation of pressure at iteration $t = 5$ for $c = 0.01$.

Table 3
Externality internalization due to peer pressure.

	Congestion delays		CO_2 emissions	
	(hrs)	($)	(tonnes)	($)
Before pressure	53,275	770,360	3,085	111,072
After pressure	15,946	230,584	2,205	79,373
Net change	− 37,329	+539,776	− 881	+31,699

NOTE: Values taken at iterations 0 and 80. Value of travel time savings of car mode, $VTTS_{car}$, taken as 14.52 "$"·h^{-1}. Social cost of carbon assumed to be $36.00/tonne under a 3% discount rate.
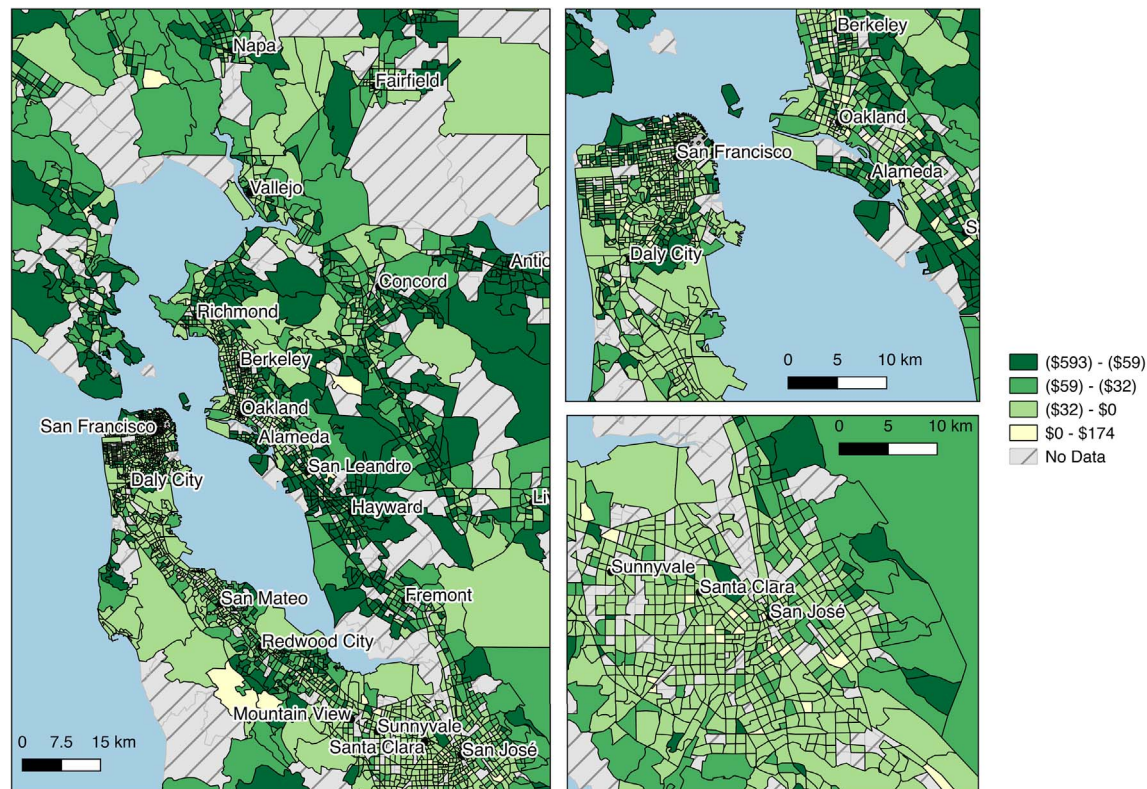
Fig. 9. Mean monetary delay costs (gains) due to difference between business as usual (iteration 0) and peer pressure (iteration 80) experienced by agents with homes in TAZs as symbolized.

memory effects in a segment of the pressured population. That is, while peer pressure-induced mode shift generally improves utility for many agents (as demonstrated by the overall increased uptake in travel mode), some pressured agents would have been better off driving. Isolating the optimal population that would benefit from pressure will be treated in future work.

The ensemble average score evolution plots (Fig. 7) present the values of the executed, worst, average, and best plans in an agent's plan set, X_{it} averaged over all agents as a function of the iteration, t. We have separated the plots of ensemble average scores into two subfigures in order to better illustrate how the dynamics of the system evolution vary with c. For values of $c < 1$, mode shift apparently covaries with score evolution, as suggested by the oscillations in scores depicted in Fig. 7a. For $c \geqslant 1$; however, Fig. 7b, indicates a catastrophic collapse in the executed and worst agent scores, with particularly unstable scores observed for $c = 10$.

The precipitous decrease in executed plan scores at high values of c clearly leads to unsustainable dynamics wherein the disutility imposed by peer pressure exceeds the utility of plan execution. The instability is most likely due to the inflexible requirement that agents who have a driving neighbor to pressure are required to pressure that neighbor no matter what the cost to themselves. Clearly this is an unrealistic scenario. We therefore present the rest of our results and analysis for simulation outputs where $c = 0.01$, which we take as a moderate value consistent with the more realistic utility scores observed for lower values of c.
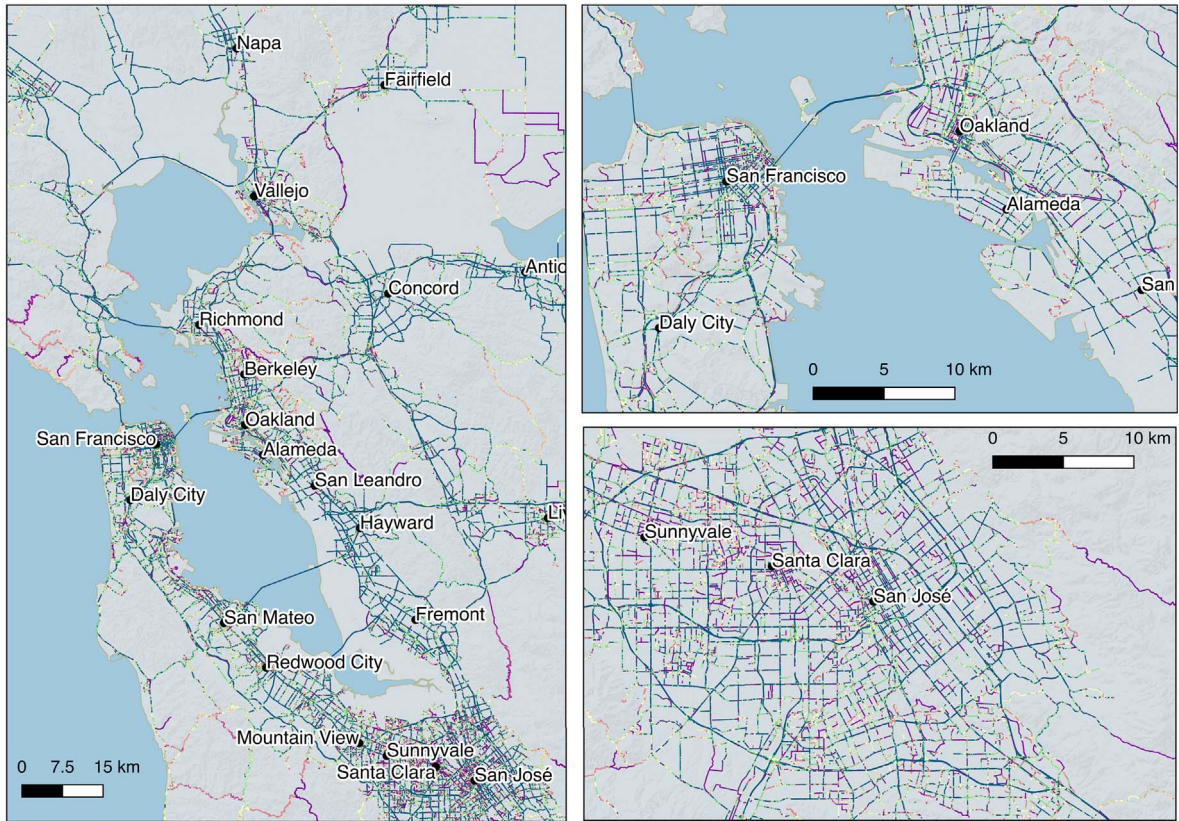
Fig. 10. Road links with improvements (shown in blue) and delays (shown in purple) based on differences between experienced and free speed travel time between iterations $t = 0$ (business as usual) and $t = 80$ (peer pressure). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5.2. Quantifying changes in externalities

Table 3 demonstrates that pressure leads to a reduction in travel delays of 37,329 h. When multiplied by the value of travel time savings (VTTS) of driving alone,[6] the reduction in delays aggregated over all vehicles for the full 24-h simulation day is equivalent to a net social gain of $539,776. The $31,699 gain from CO_2 abatement is a slightly less significant improvement. As suggested by the results presented in Section 5.1, congestion improvements are due to agents switching from driving alone to transit-oriented modes in response to the active influence of peers in their social group.

A spatial analysis of the redistribution of monetized delays is indicative of the winners and losers of peer pressure as well as where changes in travel time occur. Fig. 9 illustrates the differences in delay between the business as usual ($t = 0$) and peer pressure ($t = 80$) case experienced by agents visualized as an average over all agents with home locations in a traffic analysis zone (TAZ). Evidently, the greatest improvements in congestion due to peer pressure are experienced by people living in less populated areas. It is instructive to compare total delays experienced by agents on their individual trip routes to delays of all agents on a link-by-link basis[7] (Fig. 10). The greatest improvements happen on freeways and arterial routes, which is somewhat expected, since the greatest proportion of agents travel over these links. In some rural areas, congestion does appear to increase. Long distance commuters from the rural areas are taking more direct routes to the urban core due to the congestion relief therein, but end up queueing on the approaches. The agents traveling along these routes are unable to pressure their peers to stop driving in order to reduce congestion due to unavailability of alternative modes. This observation suggests that these users may benefit from increased access to public transit, or park and ride facilities.

We observe differences in the distributions of pressured (Fig. 11) and pressuring agents (Fig. 12). Initially, pressured agents are, as expected, clustered around public transit. However, over the course of the simulation, as feedback between pressured and pressuring agents grows, we see that presurees become more evenly dispersed throughout the Bay Area. We also observe multiple clusters of pressuring agents distant from sources of public transportation with concomitant absences of pressured agents in the same locations.

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[6] VTTS is computed as in Agarwal and Kickhöfer (2016) by taking the ratio of the marginal utility of travel time ($mUTTS$) and the marginal utility of money, β_m. The marginal utility of travel time is given by $mUTTS = \beta_{\tau,\text{mode}(q)} - \beta_{\text{act}}$.

[7] These delays are measured according to the difference between free-flow travel time and estimated travel time averaged over the 24 h simulation period.
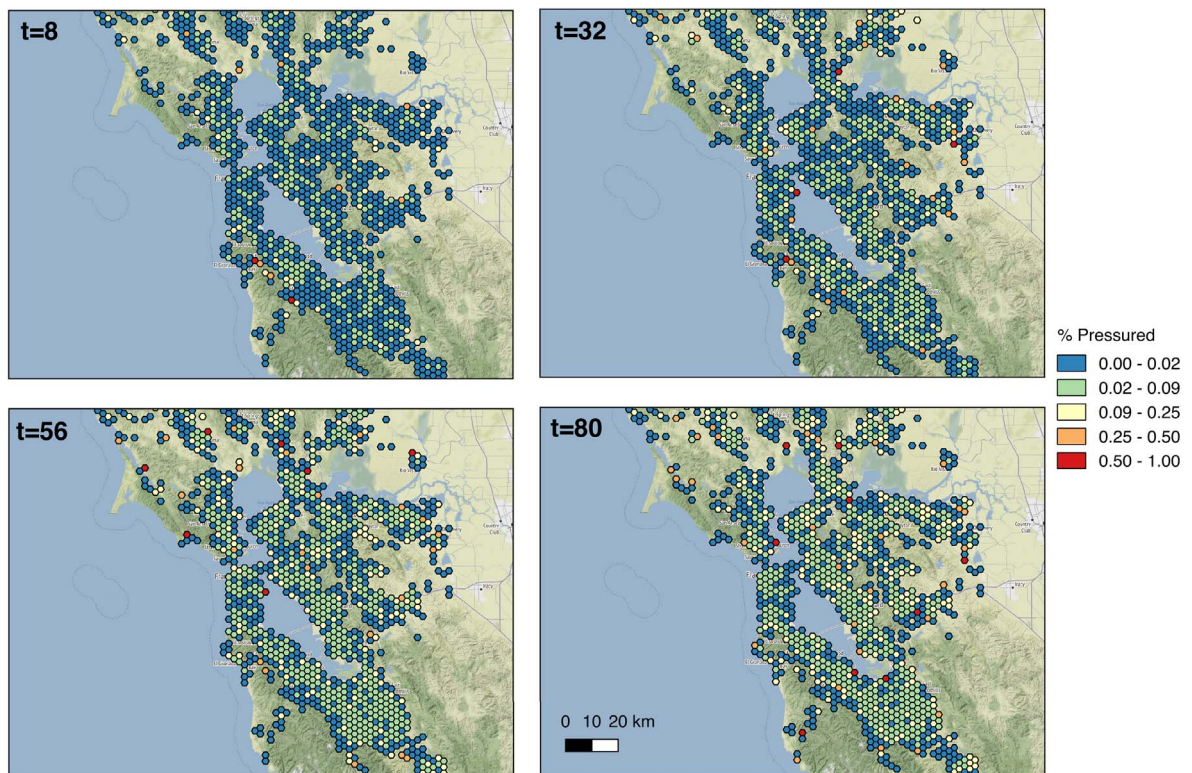
Fig. 11. Evolution of *pressured* agent spatial distribution through several iterations.
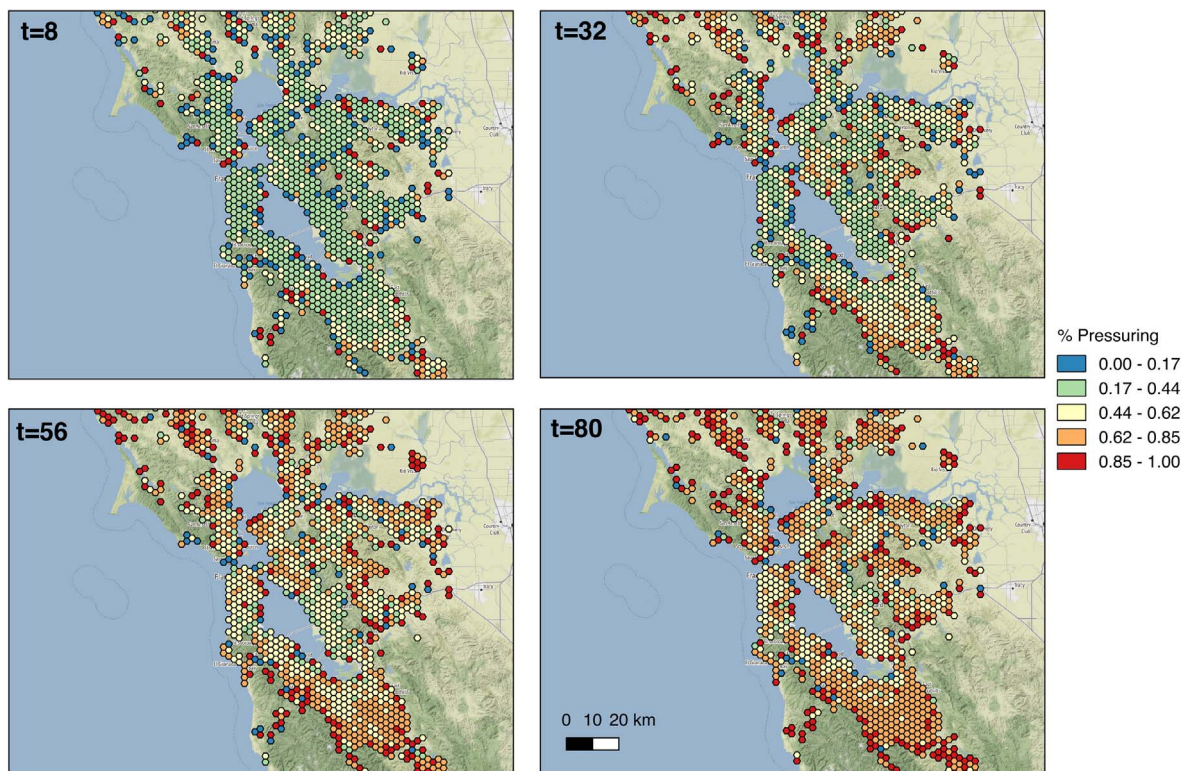
Fig. 12. Evolution of *pressuring* agent spatial distribution through several iterations.

Qualitatively, it appears that locations where agents are closer to transit seem to correspond to some of the most improved travel times (Fig. 10). In Fig. 11, we can see that, over the course of the simulation, the distribution of pressured agents becomes relatively more concentrated in these areas. More quantitative conclusions about the nature of the spatial variability of pressure and its relationship to transit accessibility in alternative transportation geographies is left as a topic for future research.

6. Conclusions

This work describes an agent-based simulation framework developed to model the effects of peer pressure on inducing socially-cooperative travel mode choice. By applying the aggregate effects of externalities on agents explicitly and providing a mechanism for agents to, effectively, negotiate time valuation, an efficient redistribution of social welfare is achieved.

Due to complex dependence of the peer pressure decisions on social network structure as well as physical infrastructure specifics such as the accessibility of socially cooperative mode choice options, the system as modeled does not admit a closed form or even approximate solution without significant simplifying assumptions. Consequently, it is not possible to develop a closed-form optimal pressure strategy for agents to pursue. The modeling framework that we wish to emphasize in this paper is more akin to that of the emerging game-based modelling (GBM) concept, as described and empirically evaluated in several recent studies (Klein and Ben-Elia, 2016; Dixit et al., 2017; Klein et al., 2018; Klein and Ben-Elia, 2017). Like those authors, we see the use of GBMs as a methodology that could help stakeholders and researchers better understand the conditions under which emergence of cooperation in a complex transportation system might be expected. The rules for our game-based model of peer pressure are not without antecedents that ensure theoretical plausibility: an analytic model of incentivized peer influence (Mani et al., 2013) and an empirically-validated agent-based simulation model of stochastic user equilibrium in transportation networks (Horni et al., 2016).

Given this modeling framework, many heuristic strategies and solution search algorithms may be explored in order to develop system-optimal pressure behavior. For example, the decision for an agent to apply pressure may be contingent on how many other neighbors the agent can pressure (as well as their pressure costs), whether other neighbors will participate, and, considering that pressure can be applied to the same person in repeated iterations, how successful past attempts were.

Despite demonstrating that peer pressure leads to widespread improvements in congestion and reductions in emissions, the spatial analysis of post-pressure changes shows that some areas are worse off. This finding highlights the need to ensure that policy proposals be sensitive to social justice issues, particularly if travel time and emission improvements are unequally biased towards one demographic or another. Running the simulation with demographic data and heterogeneous preferences accordingly may improve the representativeness of results as well as help communities understand the potential impacts of cyber-social influence.

When reduced externality costs are insufficient to encourage modality shifts away from driving, policy instruments can be used to incentivize agents to pressure their peers. However, the role of governments in achieving cooperative outcomes in social dilemmas need not be a coercive (Ostrom, 1990; Ostrom et al., 1992). In light of the analysis on incentivizing peer pressure described in Mani et al. (2013), extensions to our framework can be used to design public transportation policy that subsidizes the social costs of peer pressure with the goal of improving net social welfare. For example, a municipality can encourage positive peer pressure by providing a bonus to drivers who encourage their friends to carpool to work with them.

While designing rewards to subsidize peer pressure is a topic left for future research, the work presented herein is not without its practical merits. Simulating the positive effects of peer pressure on social welfare may motivate citizens to make decisions that equitably address commons problems by demonstrating how social networks spread and stabilize behavior change arising from local interactions. That is, by propagating simulated information from the virtual world to the real world, people can learn under what circumstances the personal cost that they incur in pressuring their peers would result in net personal and social benefits. Alternatively, our framework can be used to inform individuals if peer pressure is not worth the loss in social capital due to excessive free-riding; encouraging policy makers to fund the gap. Providing unbiased and clear information will ensure that policy nudges promote democracy rather than co-opt autonomy.

Acknowledgment

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